

MACHINE LEARNING-AIDED, ROBUST WIDEBAND SPECTRUM SENSING FOR COGNITIVE RADIOS

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14. ABSTRACT In this project, a compressive-sampling based, robust spectrum sensing approach was developed for wideband cognitive radios. The compressive-sampling based front-end is intended for overcoming the hardware imposed limitations on wideband spectrum sensing while robust detection principles are used to obtain a spectrum sensing approach that helps alleviate sensitivity to non-Gaussian noise and interference. Simulations were carried out to demonstrate that even with reduced number of samples, the proposed compressive-sampling based robust detector can indeed provide either comparable or better results to that observed with conventional periodogram, but with significantly higher number of samples. These results encourage further investigations and improvements of the proposed approach as a viable candidate for the front-end processing of a wideband cognitive radio.					
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1 SUMMARY

Compressive-sampling based, robust spectrum sensing approach for wideband cognitive radios have been developed. This project was motivated by the fact that wideband cognitive radios can be subjected to heterogeneous spectral activities from various emission sources rendering the resultant noise non-Gaussian. While conventional detectors (e.g., those that are based on least-squares estimates) can be effective against Gaussian noise, they, however, are known to be sensitive to such non-Gaussian nature of noise. Robust detection principles are used to obtain a new spectrum sensing approach that helps alleviate this sensitivity. Moreover, a limiting factor in wideband spectrum sensing is the need for higher sampling rates as necessitated by the Shannon sampling theory. In this project, a compressive sampling front-end is proposed to overcome this hardware imposed limitations on wideband spectrum sensing. Thus, the proposed approach combines a Huber cost function with an L_1 -norm constraint. The proposed compressive sampling based robust detector is indeed shown to give better signal activity detection during wideband spectrum sensing in non-Gaussian noise environments. In particular, the proposed robust method with a smaller number of samples outperforms the conventional periodogram approach in the presence of non-Gaussian noise.

2 INTRODUCTION

Cognitive radios present a potential future technology to realize autonomous radio communications over non-contiguous wide spectrum bands in the presence of adverse conditions. These adverse conditions may be both deliberate as well as inadvertent. Moreover, encroachment on previously-allocated spectrum resources by the commercial or unlicensed users and broadband-access can only be expected to grow in the coming years. Combination of these traditional as well as evolving spectrum demands requires future telecommunications technologies to be intelligent, self-aware and spectrally agile. Wideband autonomous cognitive radios (WACRs) pursued in this project are radios with these defining characteristics.

Spectrum awareness is the most salient feature of cognitive radios that makes them cognitive, and spectrum sensing is the process of acquiring spectrum awareness [1–3]. In the case of wideband autonomous cognitive radios, spectrum sensing is usually performed over several non-contiguous spectrum bands, each spanning hundreds of mega-Hertz (MHz) to even

on the order of a giga-Hertz (GHz). Due to wide bandwidth and noncontiguous nature of the frequency range of interest, an effective spectrum sensing framework for a WACR thus needs efficient spectrum scanning, accurate signal detection, as well as signal classification and identification [1]. This complete process of wideband spectrum sensing is referred to as spectrum knowledge acquisition.

In our previous work, we proposed efficient spectrum scanning by first dividing the spectrum range of interest into a set of sub-bands, where each sub-band can be much wider than a single channel assumed in narrowband spectrum sensing [1]. Hence, applying real-time Nyquist-rate sampling to detect spectral activities present in a sub-band can require large sampling rates, leading to very high computational complexity demands for associated signal processing. Another potential challenge in wideband spectrum sensing is the possible heterogeneity of electromagnetic interference (EMI) in a sensed sub-band signal. Many of these man-made interferes (e.g., jammers) are known to not satisfy the convenient Gaussian assumption used in classical signal detection approaches [4].

In this project, we make use of compressive sampling in order to reduce the high sampling rate requirements demanded by wideband sensing. When there is a certain amount of sparsity in the signal with respect to some basis, compressive sampling can be an efficient technique for reconstructing a signal that is sparse with respect to some basis (i.e., most of the expansion coefficients of the signal are zero with respect to a certain basis) [5, 6]. The efficiency afforded by compressive sampling is two-fold. First, a smaller number of samples compared to what is needed with Nyquist sampling will suffice. Second, the reconstruction of the signal from these reduced number of samples can be achieved with an algorithm with low computational complexity. We note that, in many situations sensed sub-bands will have low spectrum utilization making them sparse with respect to a frequency-domain basis. This justifies the use of compressive sampling for spectral activity detection in a wideband cognitive radio as in [7]. However, most compressive-sampling based signal reconstruction in the presence of noise commonly assumes Gaussian distributed noise. Hence, direct application of usual compressive sampling reconstruction algorithms for wideband spectrum sensing may lack robustness due to possible non-Gaussian behavior of jammers, interference, and other types of electromagnetic

radiation [1–4]. As a result, we develop a robust spectral activity detection approach based on compressive sampling for wideband spectrum sensing in a cognitive radio.

3 METHODS, ASSUMPTIONS, AND PROCEDURES

Let us consider a wide spectrum band of B Hz (where B can be in the order of hundreds of MHz to even a GHz) that is first segmented into several sub-bands. Note that each sub-band may contain several channels, possibly corresponding to different communications systems. As illustrated in Figure 1, let us assume that there are N_b sub-bands. In general, scanning of these sub-bands spanning several non-contiguous frequency ranges can be achieved using reconfigurable antennas [8].

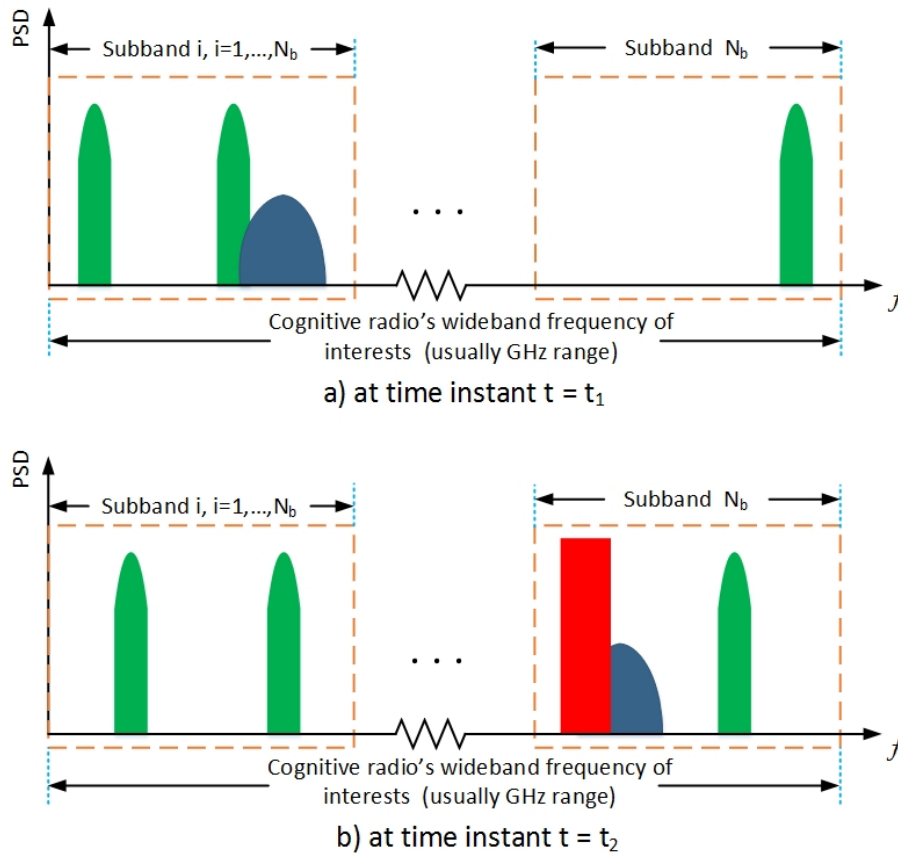


Figure 1. The Spectrum of Interest to a Wideband Cognitive Radio Divided into a Set of N_b Sub-bands

Let us denote the N -length discrete-time sub-band signal by y , where N is chosen to satisfy the Nyquist sampling criteria. The discrete frequency domain representation, y_f , of this sub-band signal can then be written as:

$$\mathbf{y}_f = \mathbf{C}\mathbf{y}, \quad (1)$$

where \mathbf{C} is an N -point Discrete Fourier Transform (DFT) matrix.

When spectrum utilization within a sub-band is low, as in Figure 1, we may expect y_f to be a sparse signal with respect to the frequency domain basis. While conventional Shannon-Nyquist sampling theory does not take into account such sparsity of signals, compressive sampling allows this sparsity property of a signal to be exploited to detect spectral activities in each sub-band with a reduced number of samples. Indeed, suppose that the sensed signal within the sub-band of interest is sparse and that we only collect an M (where $M < N$) number of randomly selected samples from the signal y :

$$\mathbf{y}_c = \mathbf{\Phi}\mathbf{y} = \mathbf{\Phi}\mathbf{C}^H\mathbf{y}_f, \quad (2)$$

where $\mathbf{\Phi}$ is an $M \times N$ random sampling matrix and \mathbf{y}_c is an M -length observation vector. As has been shown in [5, 6], if the sampled signal is sparse, then the signal y (or y_f) can indeed be reconstructed from the randomly compressive sampled (under-sampled) version \mathbf{y}_c of y by solving the following convex optimization problem:

$$\mathbf{y}_f^* = \arg \min_{\mathbf{y}_f} \|\mathbf{y}_f\|_{l_1} \text{ subject to } \mathbf{y}_c = \mathbf{\Phi}\mathbf{C}^H\mathbf{y}_f. \quad (3)$$

The lure of compressive sampling lies in the fact that there are algorithms that can solve the above optimization problem efficiently (in terms of accuracy, speed and number of samples) [9, 10]. However, (3) deals with only the ideal noiseless situation. In practice, noise is unavoidable, and thus the compressed sampled signal (2) needs to be modified as:

$$\mathbf{y}_c = \mathbf{\Phi}\mathbf{y} + \mathbf{w}, \quad (4)$$

where \mathbf{w} is an M -length arbitrary noise vector. Most previously proposed compressive sampling algorithms assume that noise, \mathbf{w} , is Gaussian. As we already discussed, however, this may not often be justifiable in wideband spectrum sensing. Hence, it is desirable to have a wideband spectral activity detector that will be able to withstand possible noise deviations from Gaussian behavior. Thus, a robust compressive sampling approach must be able to handle: 1) a nearly sparse signal, which is justifiable in at least some wideband sensing scenarios, 2) signals effected

by unknown contaminating noise which is valid for situations in which either the noise is non-Gaussian or where there is noise uncertainty (i.e., noise distribution is known only approximately).

A common model for noise with an uncertain distribution is the following ϵ -contaminated distribution [11, 12]:

$$F_\epsilon = (1 - \epsilon)\Psi + \epsilon H, \quad (5)$$

where Ψ is a known nominal distribution usually taken to be Gaussian, H is an unknown contaminating distribution that is symmetric and $0 < \epsilon < 1$ is a known parameter that determines the rate of deviation from nominal Gaussian to non-Gaussian distribution. It is known that for the noise model (5), the detector design problem can be reduced to an optimization involving the following cost function, called the *Huber* cost function, in place of the usual quadratic cost function encountered in Gaussian noise [1, 11]:

$$l_H(x) = \begin{cases} x^2/2 & \text{if } |x| \leq \delta_H \\ \delta_H \left(|x| - \frac{\delta_H}{2} \right) & \text{if } |x| > \delta_H \end{cases}. \quad (6)$$

In light of our compressive sampled sub-band sensed signal model (4), in order to obtain a good reconstruction of the possibly nearly sparse signal y_f while also combating non-Gaussian noise (5), we thus solve the following optimization problem:

$$\mathbf{y}_f^* = \arg \min_{\mathbf{y}_f \in \mathbb{C}^N} l_H(\mathbf{y}_c - \mathbf{A}\mathbf{y}_f) + \gamma \|\mathbf{y}_f\|_{l_1}, \quad (7)$$

where γ is a parameter that can be chosen appropriately to balance between the robustness against noise and the sparsity of the solution. As with (3), there are efficient algorithms that can solve (7).

In this project, we were mainly concerned with comparing the performance of the above compressive-sampling based robust spectrum estimate of the sub-band sensed signal with that of the periodogram, which is optimal if noise were to be Gaussian. However, the performance of interest is two-fold. Both the noise robustness as well as the decrease in number of used samples is of interest. In order to evaluate this performance in a simplified simulation scenario, we considered a sub-band signal y of length $N = 128$ composed of three active signals $\{x_1, x_2, x_3\}$ located at center frequencies (discrete samples per unit time) of 5, 20 and 40, respectively. The corresponding signal amplitudes were arbitrarily chosen to be 8, 15 and 22. Each signal has a

bandwidth of 7 (in discrete frequency) around its center frequency. For random compressive sampling, the sensing matrix Φ is drawn according to a normal distribution.

4 RESULTS AND DISCUSSION

Figure 2 shows the reconstruction of the above sub-band signal with compressive sampling when there is no noise using only $M=102$ number of samples. Note that, as mentioned above, these samples were drawn randomly using a normal distributed sensing matrix. Since, there is no noise, the reconstruction is obtained by solving the standard *Basis Pursuit* problem of (3) using a primal-dual algorithm [9].

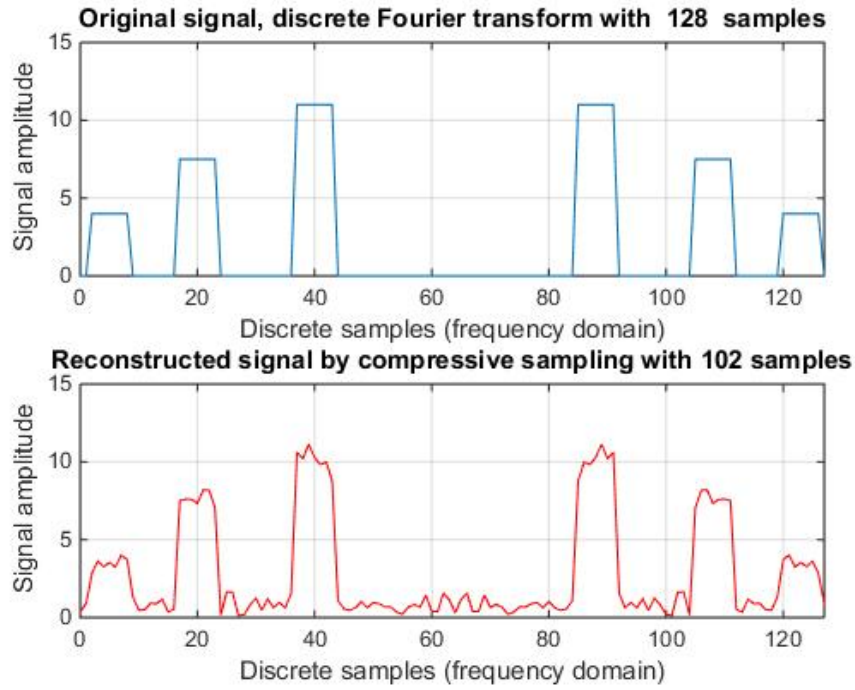


Figure 2. Original Sub-band Signal and Compressive Sampling Reconstruction of the Signal in Frequency Domain in the Absence of Noise

We may quantify the signal reconstruction performance in terms of either the normalized root mean-squared error (NRMSE) of amplitude spectrum defined as:

$$NRMSE_{Amp} = \frac{\|y_f - y_f^*\|_{l_2}}{\|y_f\|_{l_2}}, \quad (8)$$

or, alternatively, in terms of the normalized root mean-squared error (NRMSE) of power spectrum defined as:

$$NRMSE_{PSD} = \frac{\|y_f^2 - y_f^{*2}\|_{l_2}}{\|y_f^2\|_{l_2}}. \quad (9)$$

In the noiseless case of Figure 2, $NRMSE_{Amp}$ is found to be 0.2036.

Next, we introduce noise in to the above sub-band signal model. In particular, we assume that the signal is corrupted by Gaussian-Laplacian mixture noise with $\epsilon = 0.9$. The standard deviation of the zero-mean nominal Gaussian noise is taken to be 1 while the parameter of Laplace noise distribution is set to 0.2. Figure 3 shows the reconstructed signal by solving (7) as we vary the compression ratio of the number of samples from 33% to 84% (with respect to the Nyquist rate). As can be seen from Figure 3, the signal reconstruction performance steadily improves as the number of samples is increased. Importantly, even at the high compression ratio of 67%, the performance of the reconstructed signal seems to be reasonable enough for signal activity detection in the presence of noise.

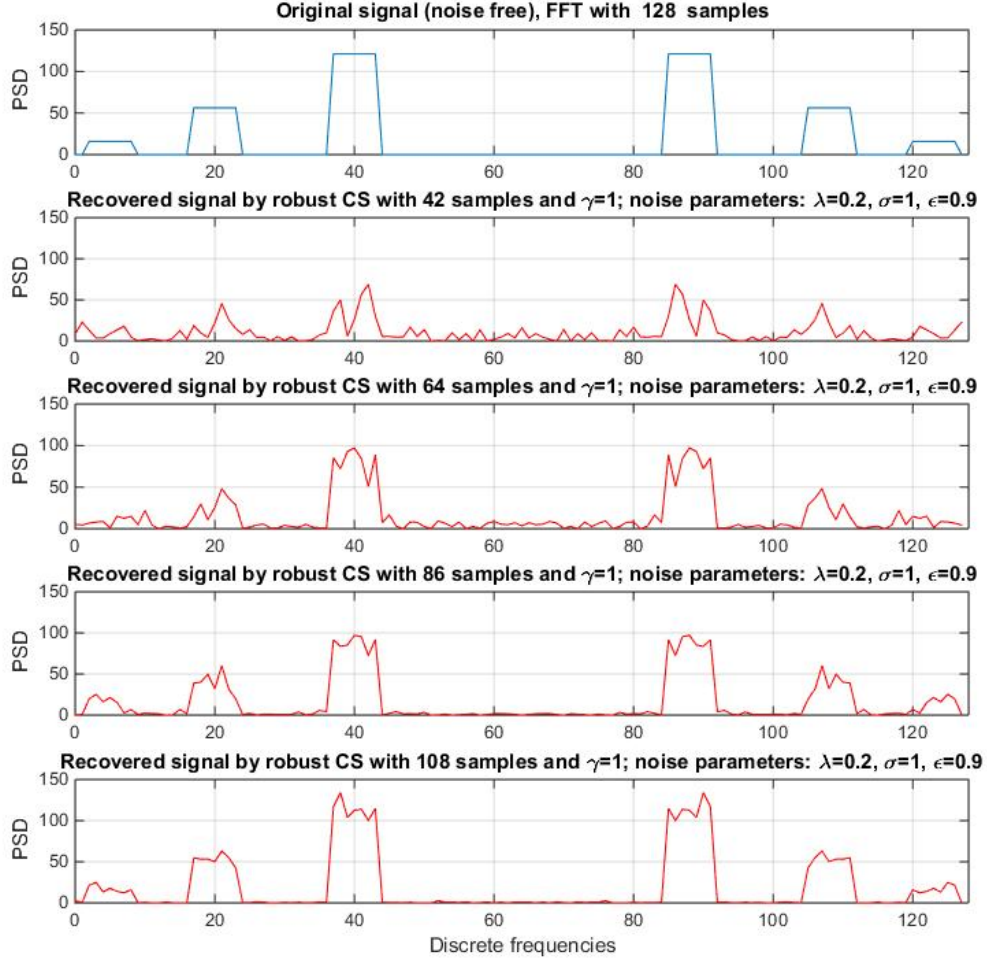


Figure 3. Power Spectral Densities (PSD) of Original and Recovered Signals by Robust Compressive Sampling (CS) with Varying Compression Ratios 33%, 50%, 67%, 84% (Top to Bottom)

It is worth comparing the signal reconstruction performance of the proposed compressive-sampling based algorithm to that of the standard periodogram. Figure 4 shows the original signal (power) spectrum along with those reconstructed by robust compressive sampling (7) using $M=89$ samples and the periodogram using 128 samples. Note that, the signal is corrupted by the Gaussian-Laplacian noise as assumed above. While still using about 30% less number of samples compared to the periodogram, the proposed robust compressive sampling

based algorithm seems to provide somewhat better reconstruction performance than the periodogram. Indeed, we found that the robust compressive sampling with $M=89$ samples gives a spectrum reconstruction with $NRMSE_{Amp} = 1.3578$, while periodogram reconstruction has $NRMSE_{Amp} = 1.4102$.

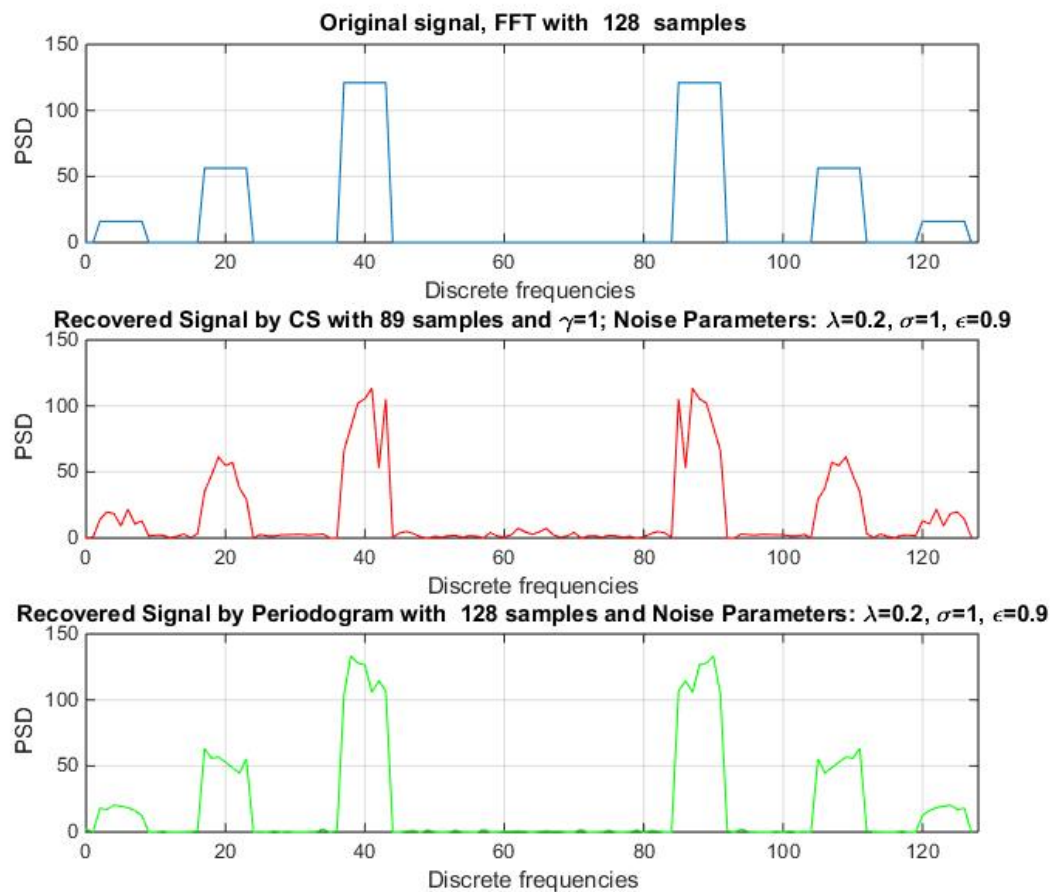


Figure 4. Power Spectra of Original Signal and Those Recovered by the Robust Compressive Sampling Algorithm (With 89 Samples) and by the Periodogram (With 128 Samples)

5 CONCLUSIONS

In this project, we developed a compressive-sampling based, robust wideband spectrum sensing approach for cognitive radios. The proposed method augments the Huber cost function with an additional L_1 -norm penalty term in order to find a sparse spectrum estimate while achieving robustness against possibly non-Gaussian noise. Through simple simulated examples, we observed that the proposed approach can improve the wideband spectrum sensing performance in two important ways: 1) the required number of samples can be reduced, and 2) the estimation performance can be better than that of the conventional periodogram. This allows us to possibly replace the usual conventional Nyquist-rate based front-end with a compressive-sampling based front-end that will facilitate real-time sensing of wide spectrum bands in the presence of possibly non-Gaussian man-made interference and other EMI.

6 RECOMMENDATIONS

The compressive-sampling based robust wideband spectrum sensing approach developed in this project is just a one component in a wideband autonomous cognitive radio system. The immediate next-step of this work is to test this algorithm on various realistic channel and spectrum conditions and refine it for satisfactory performance in real-time. The longer-term objective is to develop the other modules of the wideband autonomous cognitive radio system and finally develop an integrated complete system. Thus, it is recommended that the proposed algorithm be refined for more realistic spectrum sensing environments by incorporating machine learning techniques and then be integrated with other modules of a cognitive radio front-end processing.

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LIST OF SYMBOLS, ABBREVIATIONS, AND ACRONYMS

B	Frequency Band
CS	Compressive Sampling
DFT	Discrete Fourier Transform
EMI	Electro Magnetic Interference
FFT	Fast Fourier Transform
GHz	Giga Hertz
Hz	Hertz
L_1 -norm	Vector measurement
MHz	Mega Hertz
N_b	Number of sub-bands
NRMSE	Normalized Root Mean-Squared Error
PSD	Power Spectral Density
WACR	Wideband Autonomous Cognitive Radio

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